Qualitative response of interaction networks: application to the validation of biological models

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We advocate the use of qualitative models for the analysis of shift equilibria in large biological systems. We present a mathematical method, allowing qualitative predictions to be made of the behaviour of a biological system. These predictions are not dependent on specific values of the kinetic constants. We show how these methods can be used to improve understanding of a complex regulatory system.

There exists a wide range of technics for the analysis of high-throughput data. Following a review by Slonim [1], we may classify them according to the particular output they compute: 1. list of significantly over/under-expressed genes under a particular condition, 2. dimension reduction of expression profiles for visualisation, 3. clustering of co-expressed genes, 4. classification algorithms for protein function, tissue categorization, disease outcome, 5. inferred regulatory networks. The last category may be extended to all model-based approaches, where experimental measurements are used to build, verify or refine a model of the system under study. Following this line of research, we summary in this abstract how to define and to check consistency between experimental measurements and a graphical regulatory model formalized as an interaction graph.

1 Detecting the sign of a regulation and constraining a model

We suppose that we are given the topology of a network (this topology can be obtained from the manually-curated analysis of the literature, ChIP-chip data or any computational network inference method). In this network, let us consider a node A with a single predecessor. In other words, the model tells that the protein B acts on the production of the gene coding for A and no other protein acts on A. Independently, we suppose that we have several gene expression arrays at our disposal. One of these arrays indicates that A and B simultaneously increase during a steady state experiment. Then, the *common sense* says that B must have been as activator of A during the experiment. More precisely, protein B cannot have inhibited gene A, since they both have increased. We say that the model *predicts* that the sign of the interaction from B to A is positive.

Model	$B \rightarrow A$	$B \rightarrow^{[+]} A$	$B \rightarrow^{[-]} A$, $C \nearrow^{[-]} A$
Expression profile	B increases C increases	B increases C decreases	B increases C increases
Prediction	The action from B to A is an activation	Model and data are inconsistent	A decreases

This naive rule is actually used in a large class of models, we will call it the *naive inference rule*. When several expression profiles are available, the predictions of the different profiles can be compared. If two expression profiles predict different signs for a given interaction, there is a *ambiguity* or *incompatibility* between data and model. Then, the ambiguity of the regulatory role can be attributed to three factors: (1) a complex mechanism of regulation: the role of the interaction is not constant in all contexts, (2) a missing interaction in the model, (3) an error in the experimental source.

Let us consider now the case when A is activated by two proteins B and C. No more natural deduction can be done when A and B increase during an experiment, since the influence of C must be taken into account. A *model* of interaction between A, B and C has to be proposed. Probabilistic methods estimate the most probable signs of regulations that fit with the theoretical model [2].

Our point of view is different: we introduce a *basic rule* that shall be checked by every interactions. This rule tells that **any variation of A must be explained by the variation of at least one of its predecessors**. Biologically, this assumes that the nature of differential gene expression of a given gene is likely to affect the differential expression in other genes. Even if this is not universally true, this can be viewed as a crude approximation of the real event. We introduced a formal framework to justify this basic rule under some reasonable assumptions [3].

In our example, the basic rule means that if B and C activate A, and both B and C are known to decrease during a steady state experiment, A cannot be observed as increasing. Then A is *predicted* to decrease. More generally, in our approach, we

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use the rule as a constraint for the model. We write constraints for all the nodes of the model and we use several approaches in order to solve the system of constraints. From the study of the set of solutions, we deduce which signs are surely determined by these rules. Then we obtain *minimal obligatory conditions* on the signs, instead of *most probable signs* given by probabilistic methods.

Formally, we consider a system of n chemical species $\{1, \ldots, n\}$. These species interact with each other and we model these interactions using an *interaction graph*. The set of nodes is denoted by $V = \{1, \ldots, n\}$. There is an edge $j \to i \in E$ if the level of species j influences the production rate of species i. Edges are labeled by a sign $\{+, -\}$ which indicates whether j activates or represses the production of i.

In a typical stress perturbation experiment a system leaves an initial steady state following a change in control parameters. After waiting long enough, the system may reach a new steady state. Expression arrays provide an order of magnitude for the ratio between initial and final levels. We denote by $sign(X_i) \in \{+, -, \mathbf{0}\}$ the sign of variation of species i during a given perturbation experiment, and by $sign(j \to i) \in \{+, -\}$ the sign of the edge $j \to i$ in the interaction graph. Let us fix species i such that there is no positive self-regulating action on i. For every predecessor j of i, $sign(j \to i) * sign(X_j)$ provides the sign of the *influence* of j on the species i. Then, we can write a constraint on the variation to interpret the rule previously stated.

$$sign(X_i) \approx \sum_{j \to i} sign(j \to i) sign(X_j). \tag{1}$$

Each variable belongs to the *sign algebra* $\{+, -, ?, \mathbf{0}\}$, provided with natural arithmetic operations $+$ and $\times$ on signs. Since we are using signs instead of numerical values, the equality relation is replaced by sign compatibility relation $\approx$, ensuring that $+ \not\approx -$ [4]. This equation has to be slightly modified when the experiment is a genetic perturbation. For a given interaction graph, we refer to the *qualitative system* associated to G as the set made up of constraint (1) for each node in G.

2 Applications

When the user has a **signed interaction graph** at its disposal, the constraint equation (1) is used to validate and predict new signs variations in the network. In this case, the signs $sign(j \to i)$ in Eq. (1) are all known. This yields a system of qualitative equations with a variable $s_i = sign(X_i)$ for each specie.

We first check the **internal consistency of the network**, that is, whether there exists *at least* a value for each variation s_i such that all constraints are satisfied simultaneously.

When the system is not self-consistent, we apply a **diagnosis process** allowing to identify subsets of the network that cause inconsistency. Then the user should propose a correction of the model. This procedure was applied to *E. Coli* transcriptional regulatory network as provided in RegulonDB [5]. We deduced that transcriptional regulations are not sufficient to explain any stress perturbation of the system: complex formation implying IHF has to be taken into account.

When the system is *self-consistent*, we add perturbation data to the system of equations, fixing the value of some variables s_i. We then check the **consistency** of the new qualitative system of equation. When inconsistencies appear, we apply again our diagnosis algorithm to isolate pieces of the network that carry inconsistencies.

When the system and data are consistent, the qualitative system of equations has not only one solution but a huge number of solutions. However, some variables s_i may be assigned the same value in *all* solutions of the system. We refer to these inferred variation signs as *predictions* of the qualitative system. Applied to *E. Coli* transcriptional regulatory network including IHF complex, and corrected observations during stationary phase on 40 species, we were able to predict the variation of 381 (25%) components of our network [6].

When the user has a **unsigned interaction graph** at its disposal, we use expression profiles to test the consistency of network and infer signs of regulations. The signs of interactions $i \to j$ correspond to variables s_{ij} and each different expression profiles generate a set of variables x_i^k for species. These variables are constrained by Eq. (1). The same process as before (self-consistency, diagnosis and correction, consistency with data, new diagnosis and prediction) allows to isolate pieces of the network that are not modelled correctly and to infer signs of interaction in the remaining part of the network. Applied to several *S. Cerevisiae* networks, we obtain information on 15% to 30 % of *S. Cerevisiae* regulation signs.

On a computational background, we use Decision Diagrams and constraints programming to study the system of qualitative equations [4]. The tools are available on the web page *http://www.irisa.fr/symbiose/bioquali/*

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